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An Adaptive Neural Network Based On Model Prediction Control

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***Abstract*- Model Predictive Control (MPC) is a powerful model based control technique, which explicitly optimizes the overall performance of a system to be controlled. Also, it employs an explicit prediction model of the plant to optimize future plant behaviour. Artificial Neural Networks (ANNs), originally inspired by the ability of the human beings to perform many complicated tasks with ease, are used as an attractive tool to model complex relationships between inputs and outputs, and applied to various areas. More over neural networks (NNs) are effective models for identifying complex nonlinear and uncertain systems. Therefore neural network is suitable selection to identify complex nonlinear systems for MPC and design of training algorithm is an important task for neural network based model predictive control system. The primary intention of research is to design a model predictive control (MPC) using integration of Levenberg- Marquardt (LM) based back propagation (BP).**

***Keywords* — Model Prediction control, Artificial Neural Network, Levenberg Marquardt, back propagation.**

I. INTRODUCTION

Model predictive control (MPC) is an advanced method of process control that has been in use in the process industries such as chemical plants and oil refineries .It also been used in power system balancing models. Model predictive controllers rely on dynamic models of the process, most often linear empirical models obtained by system identification.

The main advantage of MPC is the fact that it allows the current timeslot to be optimized, while keeping future timeslots in account. MPC has the ability to anticipate future events and can take control actions accordingly. Earlier PID and LQR controllers do not have this predictive ability. MPC is a digital control. Represents the behavior of complex dynamic system and can handle large time delays and high order dynamics .MPC can predict the changes in the dependent variables of the modeled system that will be caused by changes in the independent variables.

MPC uses the current plant measurements, the current dynamic state of the process, the MPC models, and the process variable targets and limits to calculate future changes in the dependent variables. Linear MPC approaches are used in the majority of applications with the feedback mechanism of the MPC compensating for prediction errors due to structural mismatch between the model and the process. Linear models are not sufficiently accurate to represent the real process nonlinearities. In some cases, the process variables can be transformed before and/or after the linear MPC model to reduce the nonlinearity.

The process can be controlled with nonlinear MPC that uses a nonlinear model directly in the control application. The nonlinear model may be in the form of an empirical data fit (e.g. artificial neural networks) or a high-fidelity dynamic model based on fundamental mass and energy balances.MPC is based on iterative, finite horizon optimization of a plant model. Nonlinear Model Predictive Control, or NMPC, is a variant of model predictive control (MPC) requires the iterative solution of optimal control problems on a finite prediction horizon. While these problems are convex in linear MPC, in nonlinear MPC they are not convex anymore.

MPC took more time to complete the controller calculation. The choice of the model (linear /nonlinear)is crucial. Models using feedback mechanism of MPC compensating for prediction error. Linear model MPC are not sufficiently accurate to represent the real process non linearity's .Linear model of MPC algorithm results optimization problem ie., quadratic programming. Non-linear results in poor closed loop performance and instability. Non linear model used in prediction purpose will lead to non quadratic non convex and even multimodal optimization problem.

In the existing MPC based on non linear control there is no trained offline to minimize a control relevant to cost function. A non linear constrained optimization problem for MPC should be solved at each step sampling period, which lead to computationally too demanding for online implementation. Model Prediction Control is not applicable to fixed structure control process .There will be a time varying delay on stability analysis and arbitrary large control rate causes the system unstable and the system will be divergent. The main drawback of nonlinear MPC is the time processing needed to reach the optimal solution.

II. LITERATURE REVIEW

Literature presents several method for model predictive control system. Here are some of the latest methods available. Hong-Gui Han *et al*.[1] introduces a real-time model predictive control (RT-MPC) based on self-organizing radial basis function neural network (SORBFNN) is proposed for nonlinear systems. This RTMPC has its simplicity in parallelism to model predictive control design and efficiency to deal with computational complexity. First, a SORBFNN with concurrent structure and parameter learning is developed as the predictive model of the nonlinear systems. The model performance can be significantly improved through SORBFNN, and the modeling error is uniformly ultimately bounded. Second, a fast gradient method (GM) is enhanced for the solution of optimal control problem. This proposed GM can reduce computational cost and suboptimize the RT-MPC online. Then, the conditions of the stability analysis and steady-state performance of the closed-loop systems are presented.

Ramadan Hedjaz [2] have explained an adaptive neural network model predictive control (ANNMPC) where a neural model identification block is incorporated in the scheme and online update of the weights is provided when the process is subject to parameters variations and uncertainties. Simulations have been carried out to show the robustness of this control algorithm.

R. Stefan *et al*.[3] introduce fast gradient methods that allow one to compute a priori the worst case bound required to find a solution with pre-specified accuracy. They proposes to use Nesterov's fast gradient method for the solution of linear quadratic model predictive control (MPC) problems with input constraints. The main focus is on the method's a priori computational complexity certification which consists of deriving lower iteration bounds such that a solution of pre-specified sub optimality is obtained for any possible state of the system. A cold- and warm-starting strategies and provide an easily computable lower iteration bound for cold-starting and an asymptotic characterization of the bounds for warm-starting. Moreover, we characterize the set of MPC problems for which small iteration bounds and thus short solution times are expected.

Yang Wang *et al.[*4] introduces a widely recognized shortcoming of model predictive control (MPC) is that it can usually only be used in applications with slow dynamics, where the sample time is measured in seconds or minutes. A well known technique for implementing fast MPC is to compute the entire control law offline, in which case the online controller can be implemented as a lookup table. This method works well for systems with small state and input dimensions (say, no more than 5), and short time horizons. In this paper we describe a collection of methods for improving the speed of MPC, using online optimization. These custom methods, which exploit the particular structure of the MPC problem, can compute the control action on the order of 100 times faster than a method that uses a generic optimizer.

Yunpen Wang *et al.*[5] present a neuro dynamic approach to model predictive control (MPC) of unknown nonlinear dynamical systems based on two recurrent neural networks (RNNs). The echo state network (ESN) and simplified dual network (SDN) are adopted for system identification and dynamic optimization, respectively. First, the unknown nonlinear system is identified based on the ESN with input-output training and testing samples. Then, the resulting non convex optimization problem associated with nonlinear MPC is decomposed via Taylor expansion. To estimate the higher order unknown term resulted from the decomposition, an online supervised learning algorithm is developed. Next, the SDN is applied for solving the relaxed convex optimization problem to compute the optimal control actions over the predicted horizon. The proposed RNN-based approach has many desirable properties such as global convergence and low complexity. It is shown that the RNN-based nonlinear MPC scheme is effective and potentially suitable for real-time MPC implementation in many applications.

Lezana *et al.* [6] develop a finite state model predictive control strategy for flying capacitor (FC) converters. This method controls output currents and voltages and also the FC voltage ratios. This allows one to increase the number of output voltage levels, even at high power factor load conditions and without having to increase the number of capacitors and switches. Multilevel converters and flying capacitor (FC) converters are an attractive alternative for medium-voltage applications. FC converters do not need complex transformers to obtain the DC-link voltage and also present good robustness properties, when operating under internal fault conditions. Unfortunately, with standard modulation strategies, to increase the number of output voltage levels of FC converters, it is necessary to increase the number of cells and, hence, the number of capacitors and switches.

F. Oldewurtel *et al.* [7] presents an investigation of how Model Predictive Control (MPC) and weather predictions can increase the energy efficiency in Integrated Room

Automation (IRA) while respecting occupant comfort. IRA deals with the simultaneous control of heating, ventilation and air conditioning (HVAC) as well as blind positioning and electric lighting of a building zone or room such that the room temperature as well as CO2 and luminance levels stay within given comfort ranges. MPC is an advanced control technique which, when applied to buildings, employs a model of the building dynamics and solves an optimization problem to determine the optimal control inputs. In this paper it is reported on the development and analysis of a Stochastic Model Predictive Control (SMPC) strategy for building climate control that takes into account the uncertainty due to the use of weather predictions. In a first step the potential of MPC was assessed by means of a large-scale factorial simulation study that considered different types of buildings and HVAC systems at four representative European sites. Then for selected representative cases the control performance of SMPC, the impact of the accuracy of weather predictions on the control performance, as well as the tenability of SMPC were investigated. The findings suggest that SMPC outperforms current control practice in terms of both, energy efficiency and occupant comfort.

Guang Li and Michael R.Belmont [8] have explained the model predictive control (MPC) of a single sea wave energy converter (WEC). Here they using control schemes which constrain certain quantities, such as the maximum size of the feedback force, the energy storage for actuators and relative heave motion, it was possible for control to not only improve performance but to directly impact strongly on design and cost. Motivated by this fact, a novel objective function was adopted in the MPC design, which brings obvious benefits: First, the quadratic program (QP) derived from this objective function was easily convexified, which facilitates the employment of existing efficient optimization algorithms. Second, this approach was trade off the energy extraction, the energy consumed by the actuator and safe operation. Moreover, an alternative QP was also formulated with the input slew rate as optimization variable, so that the slew rate limit of an actuator was explicitly incorporated into optimization. All these benefits promote the real-time application of MPC on a WEC and reduced cost of hardware.

M. Maasoumya *et al.* [9] have explained the handling model uncertainty in model predictive control for energy efficient buildings. Here two methodologies to handle model uncertainty for building MPC. First, we explained a modelling framework for online estimation of states and unknown parameters leading to a parameter-adaptive building (PAB) model. Second, they explained a robust model predictive control (RMPC) formulation to make a building controller robust to model uncertainties. The results from these two approaches were compared with those from a nominal MPC and a common building rule based control (RBC). The results were then used to develop a methodology for selecting a controller type (i.e. RMPC, MPC, or RBC) as a function of building model uncertainty. RMPC was found was superior controller for the cases with an intermediate level of model uncertainty (30–67%), while the nominal MPC was preferred for the cases with a low level of model uncertainty (0–30%). Further, a common RBC outperforms MPC or RMPC if the model uncertainty was goes beyond a certain threshold (e.g. 67%).

Chi-Huang Lu and Ching- Chih Tsai [10] have explained an adaptive predictive control with recurrent neural network prediction for industrial processes is presented. The neural predictive control law with integral action is derived based on the minimization of a modified predictive performance criterion. The stability and steady-state performance of the closed-loop control system are well studied. The proposed method is demonstrated by stabilizing and controlling the transient response of a variable-frequency oil cooling process, a critical component in high-speed machine tools. This type of process has been widely used to provide appropriate oil coolant temperature for machine tools such as cutting, milling, and drilling machines. Such a process refers to the complicated oil-cooling procedure of the variable frequency compressor and the heat exchange system, thereby generating nonlinear and time-delay dynamic behavior. To enable good manufacturing performance of the machine tools, the temperature controller must precisely adjust rotational speed of the variable-frequency induction motor based on analog control signals.

The recurrent neural network (RNN) that consists of feed forward and feedback connections is well known to be capable of modeling and controlling nonlinear systems. Since the recurrent neuron has an internal feedback loop to size the dynamic response of a system without external feedback through delay, the RNN has shown superiority to the feed forward neural network [11], [12]. In the past decade , several researchers have extensively investigated RNN-based predictive control with its applications to industrial processes.

Min Han *et al.* [13] implement a dynamic feed forward neural network (DFNN) is proposed for predictive control, whose adaptive parameters are adjusted by using Gaussian particle swarm optimization (GPSO) in the training process. Adaptive time-delay operators are added in the DFNN to improve its generalization for poorly known nonlinear dynamic systems with long time delays. Furthermore, GPSO adopts a chaotic map with Gaussian function to balance the exploration and exploitation capabilities of particles, which improves the computational efficiency without compromising the performance of the DFNN. The stability of the particle dynamics is analyzed, based on the robust stability theory, without any restrictive assumption. A stability condition for the GPSO + DFNN model is derived, which ensures a satisfactory global search and quick convergence, without the need for gradients. The particle velocity ranges could change adaptively during the optimization process.

III. NEURAL NETWORK AND BACK PROGATION AN OVERVIEW

Identification of dynamic systems is essential for adaptive control. The definition of the adaptive system can be formulated as follows: Adaptive control systems adjust the parameters or configuration of one part of the system (controller) to the changes of the parameters or configuration of another part of the system (controlled system) so that an optimal behavior of the whole system is ensured on the basis a of the chosen criterion. Obviously, to obtain information on the dynamic behavior of the whole system - to identify it. One approach is the monitoring of the system characteristics, refinement and thus eliminating potential changes [14]. A frequently used identification method is the least-squares method. Its advantage is fast convergence of the model parameters, and storage of previous input values u, and system outputs y. The main negative feature of the methods is the computation of unreal hypothetical estimates of parameters at a short sampling period T0. A short sampling period, however, is desirable for control. At a shorter sampling period the introduced defect is more easily controlled [15]. A shorter sampling period is therefore desirable, and other identification techniques must be sought. The neural network seems to be a desirable solution because of its adaptation characteristics.

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A. Neural Approach

A formal neuron has n real inputs x1,…,xn. The inputs are evaluated using corresponding real synaptic weights w1,…,wn defining their "throughput". A neuron transforms input data into output data based on the transfer function. Individual neurons can be arranged to form a neural network – the neurons are interconnected so that a neuron output is an input to multiple neurons. The number of neurons and their interconnections in the network determine the neural network architecture. The so-called feedforward networks are used in control technology to implement controllers or, for example, to identify process parameters. In a linear model of a process it seems beneficial to use only a single neuron with a linear transfer function for identification. The advantageous and distinguishing feature of neural networks is their ability to learn. The network in the adaptive mode abstracts and generalizes the function character in the process of learning from training patterns. The learning algorithm is an optimization method capable of finding weight coefficients and thresholds for a given neural. Network and a training set. There are a number of learning algorithms. Those that are used most frequently are the back propagation (BP) algorithm and the Liebenberg - Marquardt (LM) algorithm.

B. Batch Training

The preparation of an appropriate training set is one of the major factors affecting the final training of the network. The data contained in it must sufficiently cover the problem area. A discreet description of the dynamic system can be obtained using the differential equation.

$$\boldsymbol{y(k)=b1u(k-1)+...+bnb\ u(k-nb)-a1y(k)-...-ana\ y(k-na)} \quad \textbf{(1)}$$

Where $y(k)$ is the output parameter value in the k-th sampling moment. Only the previously obtained values are used (ARX model). The identification should result is obtaining the same response of the identified configuration y and model ym to the initiation signal u. The method of preparing the training set is apparent from equation (1). In step k the vector of previous models $X = [u(k-1), \dots u(k-nb), -y(k-1), \dots -y(k-na)]$ is submitted to the network input, and trained to the current configuration response $d = y(k)$. If the network is to be used for on-line identification (control), it must be trained to more than one training pattern X, d. The batch-training principle is to create batch of p elements. For system order $n = 2$ structure of batch is

$$X = X_1 \dots X_p = \begin{pmatrix} u(n+1) \dots\dots & u(p+n) \\ u(n) \quad \dots\dots & u(p+n-1) \\ -y(n+1) & -y(p+n) \\ -y(n) & -y(p+n-1) \end{pmatrix}$$

$$\boldsymbol{d = [d1, d2, ..., dp] = [y(n+2), y(n+3), .., y(p+n+1)]} \quad \textbf{(2)}$$

In time $t = 0$ s data collection starts, $p+n+1$ steps take place (on the condition $nb = na = n$). When the batch is full, the network is trained to in this manner prepared training set. The older pattern ($X1$, $d1$) is removed in the next sample point and new pattern (Xp+1, dp+1) is added to set.

C. Back propagation Algorithm (BP)

This algorithm is based on minimizing the error of the neural network output compared to the required output. The required function is specified by the training set (a sequence of input / required network output pairs). The error of network *E* relative to the training set is defined as the sum of the partial errors of network *Ek* relative to the individual training patterns and depends on network configuration *w*

$$E= \sum_{k=1}^{p} E_k \frac{1}{2} \sum_{k=1}^{p} \sum_{j\in Y} (y_{j} - d_{kj})^2 \qquad (3)$$

Where *p* - number of available patterns, *Ek* - partial network error, *Y* - set of output neurons.
The new configuration in time $t > 0$ is calculated as follows.

$$wji\ k = wji\ k-1 - \alpha\ \partial E \partial wji \beta\ wji\ k-1 - wji\ k-2 \ (4)$$

Where $0 < \alpha < 1$ is the speed of learning, β is the momentum. [16].

The speed of training is dependent on the set constant α. If a low value is set, the network weights react very slowly. On the contrary, high values cause divergence the algorithm fails**.** Therefore the parameter α is set experimentally. If the neural network is to be used as a model in an adaptive system, for real industrial process control, the divergence must be prevented. In order to avoid it, the algorithm is often modified, the parameter α can be adjusted in the progress of training in dependence on the network error *E*. The neural network is submitted the training set patterns. The instantaneous error $E(w(k))$,$\partial E(w(k))\ \partial w(k)$, is determined, and a new weight configuration $w(k+1)$, then $E(w(k+1))$ are calculated. Now, we have to find out if the network training error was reduced. If

$$\boldsymbol{E(w(k+1)) < E(w(k))} \ (5)$$

Is fulfilled, the new configuration of network eights is accepted, the value of parameter α is increased. Otherwise constant α is decreased and configuration $w(k+1)$ is recalculated.

IV. LEVENBERG-MARQUARDT ALGORITHM (LM)

This algorithm is a variant of the Gauss-Newton optimization method. The new configuration of weights in step k+1 is calculated as follows

$$\boldsymbol{w(k + 1) = w(k) - (J\ T\ J + \lambda I)-1\ J\ T\ \varepsilon(k)\ (6)}$$

The Jacobi's matrix for single neuron can be written as follows:

$$J= \begin{pmatrix} \frac{\partial_{\varepsilon_1}}{\partial_{w_1}} \cdots \frac{\partial_{\varepsilon_1}}{\partial_{w_n}} \frac{\partial_{\varepsilon_1}}{\partial_{w_0}} \\ \vdots \quad \vdots \quad \vdots \\ \frac{\partial_{\varepsilon_p}}{\partial_{w_1}} \cdots \frac{\partial_{\varepsilon_p}}{\partial_{w_n}} \frac{\partial_{\varepsilon_p}}{\partial_{w_0}} \end{pmatrix} \begin{pmatrix} x_{1_1} \cdots x_{n_1} & 1 \\ \vdots \quad \vdots & \vdots \\ x_{1_p} \cdots x_{n_p} & 1 \end{pmatrix} \qquad (7)$$

Where is *w* - vector of the weights, w0 - bias of neuron, ε - error vector (the difference between the actual and the required value of the network output for the individual pattern).

Parameter λ is modified based on the development of error function *E*. Should the step cause a reduction of *E*, we accept it. Otherwise we change parameter λ, reset the original value and recalculate $w(k+1)$ [17].

V. CONCLUSION

The primary intention of research is to design a model predictive control (MPC) using integration of Liebenberg Marquardt (LM) based back propagation (BP) and group search optimization. Generally, model predictive control (MPC) is a powerful model based control technique, which explicitly optimizes the overall performance of a system to be controlled. Also, it employs an explicit prediction model of the plant to optimize future plant behavior.

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